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An agent-based model of consumer mobility in a retail environment

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Abstract

In a retail environment it is nowadays crucial to take into account recent trends and evolutions in consumer mobility behaviour in order to align the actual implementation of operations management decisions with the company's consumer-centric strategy. We aim to bridge the discrepancy between the assumptions behind the analysis for supply side decisions and the modelling of the demand side mobility behaviour that still exists in theory. With an agent-based approach to consumer spatial behaviour we study the impact of increasing mobility of consumers on the logistical strategy of retailers.
In an artificially generated world imitating the spatial configuration of a big city, we study different scenarios about consumer mobility. We focus on the impact of commuting behaviour and on the resulting effect of different cognitive maps that influence a consumer's store choice. We do not only study the model's numerical results but also throw a look on the spatial outcome.
The main result is that we provide greater insight in emerging retail location patterns as a result of changing consumer spatial behaviour and that this interplay between consumer mobility and location strategies can be thoroughly studied with an agent-based modelling and simulation approach.

Selection and/or peer-review under responsibility of the Organizing Committee.
Keywords: mobility, retail, location strategy, agent-based model.

1. Introduction

Consumers are becoming more mobile and travel more both for pleasure and business (Douglas & Craig, 1997). This is one of the research perspectives identified by Dion & Cliquet (2006): "a geographic space should not be defined according to the individuals who reside or work there, but also by thinking of those who pass through it". The increased mobility of consumers implies that not only stocks of clientele, but also flows should be taken into account, therefore we echo the call of Dion & Cliquet (2006) about "integrating the intensification and increasingly complex nature of consumer mobility" in store choice models that are at the base of location models for retailers.

It is not self-evident to tackle this challenge with proven techniques to model consumer mobility. The conventional 4-step model (FSM) for traffic forecasting stems from a trip-based approach (McNally, 2000). The trip generation, trip distribution, modal split and assignment are four separate stages in one model. With the more recent activity-based approach, the actual travel behaviour is taken more explicitly into account. However, the point of view is still on an aggregated level which is not always well-suited for real-world applications (Balmer et al., 2004).

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To address the complex nature of consumer mobility we propose an agent-based approach (Macall and North, 2010).

We first introduce the problem definition. Next we describe the core components of the conceptual model that will be implemented in the next section. We generally specify the environment and the actors in the simulation, together with their attributes and their behaviour.

1.1. Problem definition

With an agent-based simulation approach for consumer mobility we envision to gain insight in emerging retail location patterns as a result of changing consumer spatial behaviour.

Although we immediately start with a complete model of supply and demand side in a retail market, we focus in first instance on the demand side. Mobility of individuals plays an important role in the shopping behaviour of consumers. From a case study in Ghent (Belgium) it is clear that consumer mobility in terms of commuting behaviour creates significant opportunities in the context of shopping behaviour: more than two third of the commuters purchase groceries on the way home (Vanhaverbeke, 2010). To practically fill in the broad concept of mobility, we focus on the commuting behaviour of work-active consumers. We expect that changing the rules of shopping behaviour outside or during commuting trips will lead to different location patterns of the retailers. This is a first effect we seek to mimic.

Next to mobility, we also aim to incorporate bounded rationality in consumer spatial behaviour modelling. A specific element herein is the concept of a cognitive map. In the store choice context, we can more specifically define a cognitive map as "a representation of physical structures of the city including the shopping opportunities and facilities" (Drezner, Eiselt, 2002). The fact that the cognitive map does not perfectly correspond to the objective representation of physical structures of the city including the shopping opportunities and facilities is due to the fact that distance and travel time are based on the consumers' perceptions instead of being based on objective observations. Every consumer in the simulation has his or her own cognitive map and by changing the rules to populate the map with retailers, we expect again to see different location patterns of the retailers. We will apply two types of changes with respect to the construction of cognitive maps: we limit the size of the cognitive map in one stage and in the following stage we enforce social interactions among consumers that allow them to share information and expand their cognitive maps.

So far the focus was on the demand side. In the last stage of the iterative model development, we will increase the complexity of the retailers' environment by introducing differentiation in assortment. Through being present with different store formats at different locations, the retailer can try to respond to the needs that the consumer encounters at that location (city centre or suburb), and maybe even at that moment (lunch time, weekend), by carefully selecting non-homogeneous products across the store formats. This is already happening for example in the context of traditional supermarkets, evolving more into a chain of convenience stores in the city centre, supermarkets at the outskirts of the town and hypermarkets near highway exits. We expect this differentiation policy to affect both the retailers' location strategy and the consumers' behaviour. By running the simulation for the different cases specified above, we expect to obtain a view on the interplay between consumer spatial behaviour and retail location decisions.

1.2. Conceptual model description

Figure 1 visualises the agent types that we will take into account and their interaction with other elements in the system. On the right-hand side we see the representation of the supply side. While they are in competition with other retailers, the retailers under study need to decide on their location strategy. Therefore they take into account the consumer spatial behaviour of the households. On the left-hand side of the figure the demand-side is visualised. The households interact with each other through word-of-mouth effects. By specifying relevant attributes and behaviour for retailers and consumers at micro-level, we expect location patterns to emerge as an outcome of the simulation.

Concerning the demand side, we distinguish between two types of consumer agents: the residing consumer who does not show commuting behaviour and the work-active consumer who commutes every day. The consumer agents display spatial behaviour for shopping and, in case of work-active consumers, for commuting. Shopping behaviour is triggered when the consumer's groceries stocked at home run out. When he needs to go shopping, the consumer considers the retailers in his or her cognitive map and patronises the most attractive retailer. By implementing the concepts of commuting mobility and cognitive map in the consumer behaviour we will be able to address the first two questions specified in the problem definition.

With respect to the supply side, there are also two types of store agents: the competitors and the retailers of the chain under study. We assume that we need to solve a location problem for one retailer chain who enters a market in which competitors are already active. The competitors are thus operating agents in the simulation and we nominate the potential locations for our retailer chain as retailers. In the course of the simulation a given number of retailers will decide to actually open and be operational.

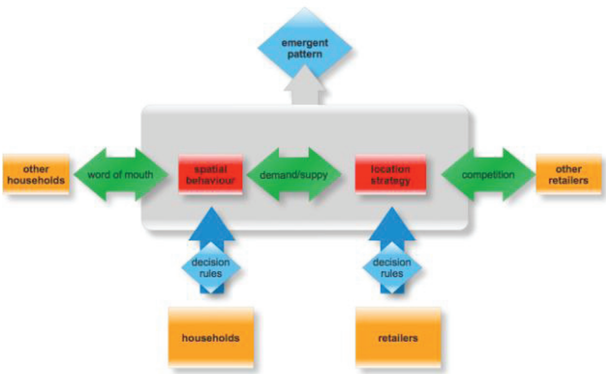

Figure 1 Schematic representation of conceptual model.

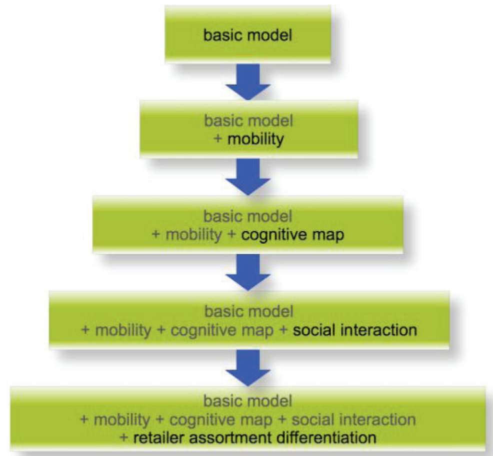

Figure 2 Incremental stages in the prototype model development.

We work according to the well-established tradition of incremental development. To gradually increase the complexity of our model, we iteratively build upon a basic version of the model. Starting with simple assumptions, each development stage adds new capabilities to the model and expands the range of questions that it can answer. This is schematised in figure 2.

We start with a simple situation. Initially, in the first stage, we do not implement heterogeneity in the attribute values for the agents, except for their locations. The most important restriction here is that consumers can only shop when they depart from home; this implies that commuting consumers must first return home after work and then can go shopping. A problem with these assumptions can easily be solved with the classical maximal covering location (MCLP) model (Church & ReVelle, 1974) . Taking the data from our artificially generated world, we will run the optimisation model and use the result as a benchmark for the following stages. Next, still in the first stage, we introduce heterogeneity among the consumers and retailers by differing the values of their attributes, which also creates chance variation in their behaviour.

In a second stage, we allow the work-active consumers to go shopping while they are on the way home from work. The consumers do not need to go home first before stocking up on groceries.

To further elaborate on the concept of bounded rationality, we change in a third stage the shape of the cognitive map of all work-active consumers and study the impact for the retailers. So far, the cognitive maps of the consumers were populated with retailers in the neighbourhood of the residence, and, in case of work-active consumers, near the workplace and the road from home to work.

In a fourth stage we add social links among consumers so that they can exchange information about the retailers they have knowledge of.

In a fifth stage we add heterogeneity to the retailers in terms of their assortment. In practice it is clear that convenience stores have a different assortment than the traditional supermarkets. We distinguish between two types of retailer stores: the convenience stores where especially fresh goods are sold and the traditional stores where all types of groceries are part of the assortment.

As a result of this iterative development procedure we end up with a fairly complex model.

For the definition of the world, we take into account the remark of Jager (2006) that “in more complex spatial models it would also be possible to include a spatial density of the location of the agents, thus allowing for distinguishing between more rural and urban areas”. The remark was made in a framework about consumer behaviour in general and the author pointed out “it is expected that such sophisticated models are more appropriate to address issues such as shop location planning”. Given that this is exactly our situation, we have indeed mimicked the spatial configuration of a big city: the centre of the world is mainly populated with working places for commuters and around the centre the consumer population is denser to represent the suburbs.

We develop our model in a virtual world with randomly generated data. Obviously this has implications for the validation of the model and we will come back to that in section 5.

We have now described a conceptual model to take an agent-based approach for the impact of consumer mobility on retailers’ location strategies. In the next section we specify in detail how the conceptual model is implemented for the actual simulation.

2. The simulation setup

The proof-of-concept of our approach is programmed in NetLogo 4.1 (Wilensky, 2009) on Mac OSX (2.16GHz Intel Core 2 Duo with 2GB DDR2 memory). In NetLogo lingo agents are called ‘turtles’. These ‘turtles’ can move over a grid of stationary agents, called ‘patches’. Our simulation world consists of a two-dimensional grid of 100 x 100 patches, i.e. individual squares in the grid with fixed coordinates. Although it is possible in NetLogo to wrap the world around the edges, we opt for a non-wrap topology and calculate straight-line distances accordingly.

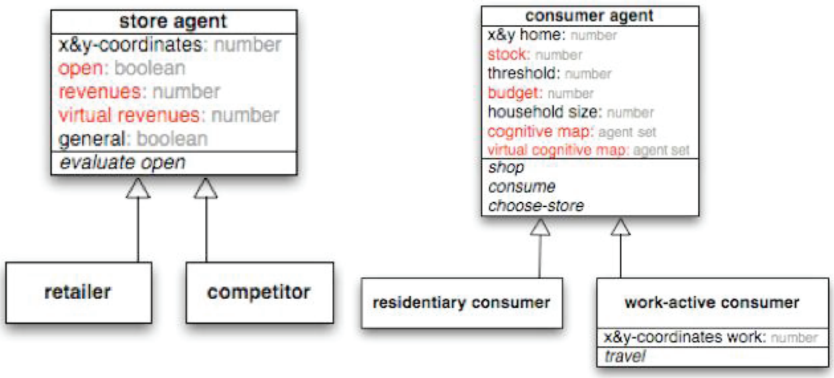

Figure 3 Store agent class & Consumer agent class

To model the supply side, we define store agents: the retailers of the particular chain under study and the competitors (belonging to all other chains on the market). In figure 3 the attributes and the methods for store agents are listed. The coordinates specify the store agents location; the open attributes indicates whether a store is opened or not; the revenues and virtual revenues are the amounts spent, virtually or not, in the stores; and the general attribute concerns the assortment offered by the store. The attributes indicated in red vary during the simulation; the other attributes have fixed values.

Initially, the values of the attributes ‘revenues’ and ‘virtual revenues’ are set to zero.

We are particularly interested in the behaviour of the retailers since they are the decision makers for the location problem. All retailers are closed at the start of the simulation. We already mentioned that his means that the locations of the retailers actually represent the potential sites to open. They are randomly distributed on the grid and we assume that the retailers are fixed to their assigned location during the entire simulation.

The competitors do not move either. At the setup of the simulation all competitors are open and they do not close during the simulation. All store agents are located on non-coinciding patches.

The store agents behaviour:

- revenue making behaviour: In the decision-making simulation retailers are attributed virtual revenues. When consumers need to shop, they keep the same quantity in mind as they would buy in the already opened store. For all the retailer agents in their virtual cognitive map – regardless whether these stores are open or closed – that fulfil their needs at that particular time and place within the given maximum distance, the consumer allocates the sum required to buy the quantity he had in mind at that respective store. More specifically, the retailers more attractive – closer – than any opened store (retailer or competitor) within the given threshold distance receive the price of a product unit times the wanted quantity, in other words an adopted amount of what the consumer is about to spend elsewhere, as virtual revenues. In this manner, all retailers keep track of their potentially foregone revenues when they are not open.
- site opening evaluation behaviour: At the end of the first period, the retailer chain management applies a greedy procedure and allows one retailer to open, being the retailer with the highest virtual revenues. Then, we reset the virtual revenues of all retailer agents, simulate another period, and apply the greedy procedure again. The next retailer opens, being the one with the highest virtual revenues but with the additional constraint that the new site is not too close (outside a given perimeter) to the previously opened retailer. This 'forbidden to locate in the near neighbourhood' rule is included to prevent cannibalisation.

Next to the two types of store agents – retailers and competitors –, we also distinguish two types of consumer agents: the residentiary consumers and the work-active consumers. Figure 3 shows the attributes and methods for the consumer agent class.

Residentiary or home-based consumers stay at home all day. This is obviously an oversimplification of real behaviour, because this group of consumers (e.g. the retired, the unemployed, housewives, ...) actually do undertake leisure trips, multi-purpose shopping trips, ...Yet, we assume that the majority of the shopping trips depart at home and therefore we do not take into account other spatial activity.

The work-active consumers leave for work in the morning and come back home later that day. This, too, is an oversimplification: the trips of work-active consumers from home to the office are spread over the day and some might even go have lunch at home during lunch break. The workplaces are randomly distributed within a given radius around the four quadrants' inner corners. Work-active consumers are randomly assigned to a workplace.

Note that this configuration implies that we are investigating the case for a big city: people are housed in the suburbs and work in the business buildings at the centre of the town.

We further assume that the consumer agent is the representative buyer for a household. This means that all the attributes are indicators at household level. Both the residentiary consumers and work-active consumers have a household size and a household budget as well as a stock of groceries and a minimum threshold on that stock.
Consumer agents have limited knowledge of their spatial environment. We use the concept of cognitive maps to determine the choice set of store agents for every consumer. The consumers are aware of all the open stores in a given radius around their homes. On top of that, the work-active consumers know the stores in the same radius around their workplaces and they are also aware of the stores in a corridor with width equal to the given radius along the shortest path they take from home to the workplace. The cognitive map of consumers does only contain opened stores. We also generate a virtual cognitive map for every consumer in which all the stores, open or closed, are stored – the exact purpose of this virtual map will be explained below.

The consumers' behaviour:

- consuming behaviour: Each consumer agent keeps track of his stock of goods and once the stock level drops below the consumer agent's predefined threshold of stocked goods, he needs to go shopping. Consumers (households) daily consume around noon a fixed number of goods times the household size and this action decreases the stock of goods. We have modelled the need to go shopping as an increasing linear function dependent on the time passed after the threshold is crossed and within 24 hours (48 ticks) after the minimum threshold is crossed, if not earlier.
- shopping behaviour: The shopping routine involves choosing a store and spending money to replenish the stock of goods. Shopping consists of choosing a store and spending money.
- store choice behaviour: Firstly, a store to patronise is chosen. The consumer scans his cognitive map and selects one store according to an utility function. In the first prototype model stage, for example, we consider distance as the single criterion and, obviously, the consumer minimises his utility function. Consumer spatial behaviour

theory also states that a threshold distance is considered. In case the selected store is within a given maximum distance, the consumer actually moves to the selected store.

- money spenditure and stock replenishment behaviour. This is a function of a constant number of goods times the household size. Spending money depends on the available budget of the consumer. First the number of units to shop for is determined, then the cost of this basket is calculated. If the consumer can afford the whole basket, it is purchased. The consumer's budget decreases with the amount to pay. If the consumer is almost out of budget, he buys the number of goods proportional with what he can afford. Finally, the consumer pays for the goods and adds the bought goods to his stock at home.

3. Running the simulation

First we describe the general information relevant for running the simulation. Then we take a look at the two types of simulations we will perform: the decision-making simulation and the solution quality assessment simulation. This thorough description of the simulation run will allows us to punctually present the results of the model in the next section.

3.1. General information

The simulation runs by the increase of so-called time steps. We assume that one time step represents half an hour and the choice of the time step length is based on the short-term decision making processes of the consumers. We note that the location strategy of the retailers is a long-term decision, which implies that we have to run the simulation for a considerably large number of time steps.

The consumers are active from 6 am until 10 pm. This means that they travel, shop and – in the case of work-active consumers –work in this time interval. Although this is momentarily not really crucial to incorporate in the prototype model, we have foreseen this feature because the decision on the opening hours for the retailers can be drastically influenced by this time aspect of consumer behaviour. We also specify the speed with which consumers move in the world and we define that commuting trips in the virtual world do not last longer than 2 hours.

We run two types of simulations: one in which the retailer's decision(s) about which site(s) to open is made and another to assess the quality of the solution from the first simulation. The latter allows to compare – for the basic case – with the result of a MCLP model on the one hand and to estimate the impact of an added complexity element on the retailers' revenues on the other hand.

3.2. The decision making simulation

In the decision-making simulation, the retailer chain decides where to locate a given number of stores. We consider the case of locating three stores in this prototype model.

To simulate the location strategy behaviour of the retailers, we first generate information on which the location decision will be based. We apply an often-used technique from market research: we mimic the 'traffic study' approach. In practice, the feasibility of an interesting location for opening a retail store is sometimes investigated through traffic monitoring. A market researcher physically positions himself at the entrance of the store-to-be and during different moments of a day and/or week counts the number of cars or pedestrians passing by. We simulate this kind of study by first observing the behaviour of the consumers for one month and then sequentially open retailer agents based on that information. Thus to start, the simulation is run for 1 month, during which the consumers show their consuming and shopping behaviour.

This process is repeated until the given number of stores to open are actually opened.

The result we are interested in, from this simulation, is where the retailers open. As we do not have all the information yet to make a complete estimation of the expected market share for the retailer, we will use the information about where to open retailer sites to run the next type of simulation, which assesses the quality of this first simulation solution.

3.3. The simulation for assessing the quality of the solution

Because the decision-making simulation does not generate actual revenues from the start and consequently does not allow us to analyse the location solution as a whole, we run a second evaluation simulation not only to compare the final results of the simulation with an analytic model solution in terms of actual opened locations, but also to compare the resulting total revenues (in relative terms) for the retailer chain across the different simulations with a good benchmark.

We do the simulation again, but now the selected retailers from the previous simulation and all the competitors are open from the start of the simulation. During the simulation the store agents' size evolves proportionally with his revenues. Ultimately we are interested in the market share for the retailers, which we specify as the proportion of the total amount of actual revenues generated for the chain of retailers divided by the total consumers' expenditures throughout the simulation.

We start with a simple model and then increasingly complicate the behaviour of the agents. In the next sections, we first run simulations of an environment that could also easily be modelled and solved with an analytical approach. We compare the simulation results with the optimisation model results. As we gradually increase the complexity of the environment and the agents' attributes and behaviour, it becomes harder and harder to solve the analytical models. That is where the added value of the agent-based methodology is shown to its full extent.

4. Simulation results

In this section we respectively report on our base case and the following iterative development stages for which the relevant changes are implemented and the resulting impact on the model outcome is studied.

Dedicated shopping trips with spatial proximity preference.

We start with a very basic, close to rational consumer behaviour. The conditions for a retailer to be allocated the virtual revenues is that the store needs to be in the cognitive map, within the maximum distance that the consumer is prepared to travel, and the store must be closer to the consumer than any other opened store (retailer or competitor).

Initially we have eliminated from the model all random factors that cause consumer or store agents to be heterogeneous in their attributes or in their behaviour. To go shopping, consumers must depart from their residences. This type of problem can also be solved with the MCLP with input of the same data.

We schematised the starting values for the agents' attributes and the world variables in Figure 4.

In Table 1 we present an overview of the different scenarios and the results, which are also visualised in Figure 5.

Table 1 Overview of simulation results

Scenario	Results
Base case – Fig. 5(a)	Market share retailers: 25%
Base case incl. randomness	Market share retailers ↑: 27%
Stage 2 (+ flow-by shopping) – Fig. 5(c)	More central locations + market share ↑: 32%
Stage 3 (+ limited cognitive map) – Fig. 5(d)	Market share ↓: 25%
Stage 4 (+ social interaction) – Fig. 5(e)	Market share ↑: 32%
Stage 5 (+ heterogeneous stores) – Fig. 5(f)	Double # retailer locations + market share ↑: 46%

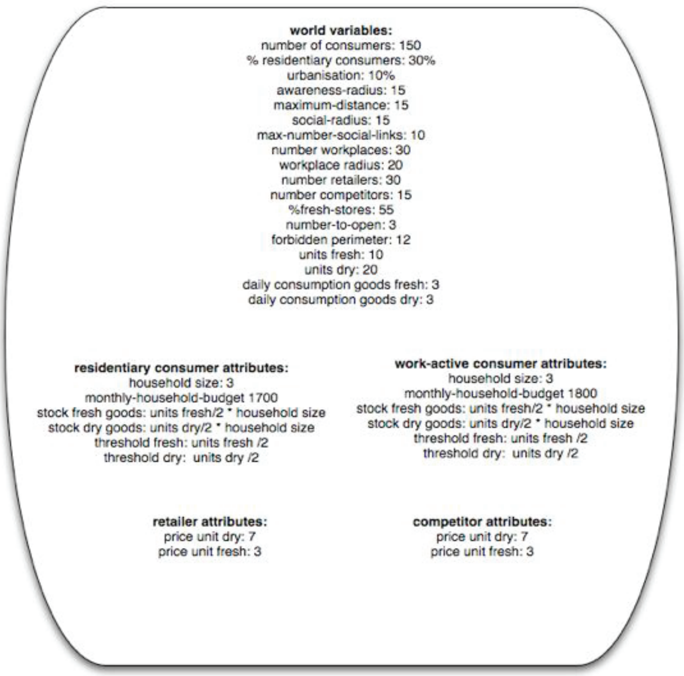

Figure 4 Initial values

Note that when we solve the base case analytically to optimisation, it is remarkable that the maximal covering model solution is spatially similar to the simulation outcome and the market for the retailers is 24%, a slight difference we ascribe to little variation in purchasing behaviour. The greedy procedure seems to perform very well as a proxy for the location problem. This is in line with the fact that "greedy-type heuristics are known to perform extremely well in many location problems, in particular for flow interception models" (Berman & Krass, 1998).

4.1. Comments on the simulation results

We have discussed the results of one simulation in particular to provide insight in the emergent location patterns resulting from changing consumer spatial behaviour and heterogeneity among the store agents. We have seen that consumer mobility effectively impacts the spatial configuration of opened locations as well as the revenues of the retailer chain. Also the effect of differently shaped cognitive maps was clearly observable in a different spatial configuration of the opened retailers and in the decrease of the retailer chain's revenues. Finally, the non-homogeneity of products in the assortment of the retailers leads to a pattern of openings in the centre of the virtual world by traditional general retailers and their fresh counterparts open elsewhere. With this prototype simulation we have shown how addressing challenges in modelling consumer spatial behaviour provides insight in emerging location patterns. Obviously, this one particular instance of the simulation does not allow us to draw general conclusions. We are very much aware of the current verification and validation issues herewith related and we address these in the next section.

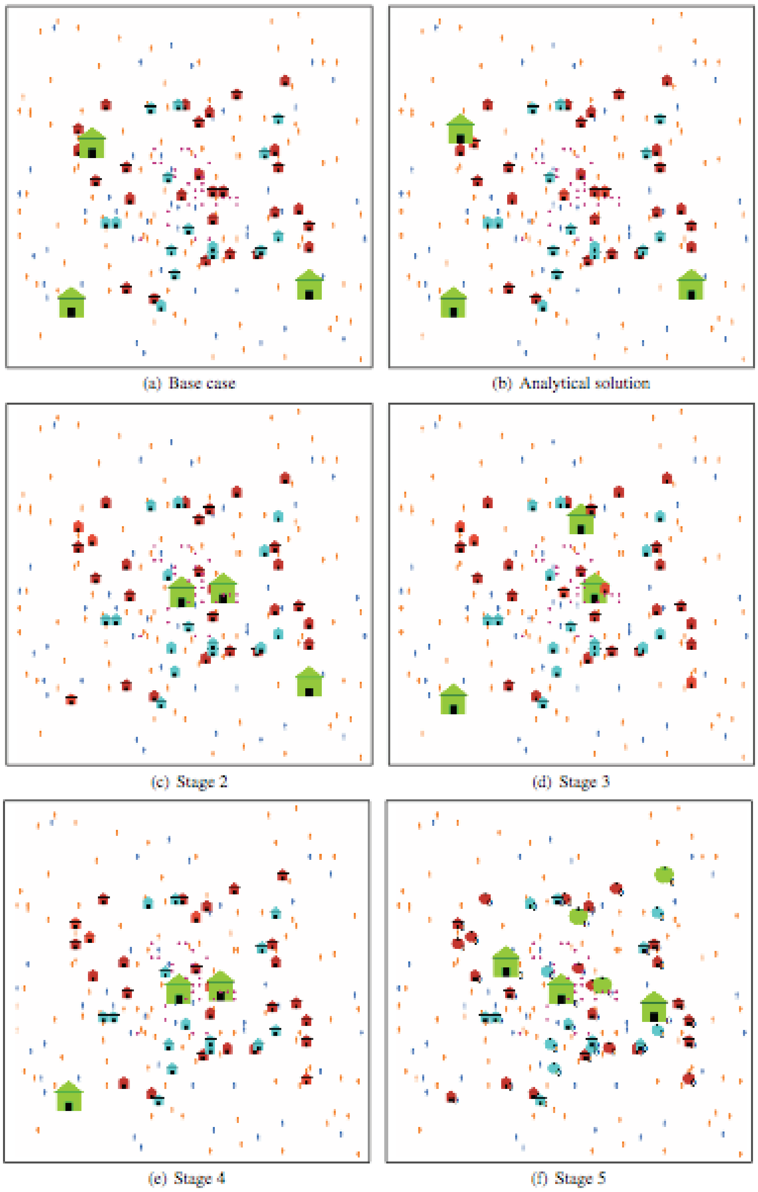

Figure 5 Spatial representation of the results

5. Validation

We agree with Midgley et al. (2007) that "the relatively new and important approach of ABM and its developments are encouraging to those who believe that many human systems are complex, non-linear and exhibit emergent behaviour, and are thus poorly modelled by the existing approaches", but we also humbly recognise that the validation of the ABM results remains a big issue.

Concerning the validation, a good question to start with is formulated by Marks (2007): "What is a good simulation? The answer to this question must be: a good simulation is one that achieves its aim."

In our particular case, we refer to our problem definition and we recall that our intention was to gain insight in the interplay of consumer spatial behaviour and retail location decisions. Given the conclusion of the previous section, we consider our aim achieved. However, we immediately add that we only developed a prototype model and that there remains a lot to be done in terms of testing the robustness and the sensitivity of the model, e.g. by sweeping the parameter space of the agents' attributes and the world variables.

We therefore frankly second the statement by (Fagiolo et al., 2007) that "in order to compete with mainstream neo-classical models, ABMs have to confront empirical evidence and be better able to reproduce and explain existing observations". Although we could have based and calibrated our simulation model on the data from a case study on consumer spatial behaviour in Ghent (Vanhaverbeke, 2010), unfortunately we did not have access to supply side data essential to fully validate our prototype. We thus choose to work with an artificial world.

In Marks (2007) a general framework for validating simulation models is presented. The author agrees with Moss & Edmonds (2005) that for AB models there are at least two stages of validation. The first stage is the micro-validation of the behaviour of the individual agents in the model and the second stage is the macro-validation of the model's emergent behaviour when individual agents interact.

We have closely monitored the behaviour of the agents. By carefully examining this visual information in combination with the output on the monitors in the model interface, we verified the consumers' behaviour.

Next to the micro-validation, we also looked at the dynamically formed patterns. The emerging behaviour of the system was in line with our initial expectations. We also compared the outcome of the agent-based approach with the solution of the optimisation model for the first scenario.

In terms of comparing models, Marks (2007) refers to Axtell et al. (1996) who introduced the term 'docking' for the attempt of another team to replicate a simulation model. Three decreasing levels of replication are numerical identity, distributional equivalence (results not statistically distinguished) and relational equivalence (same qualitative relationships).

We did not apply the docking strategy, but it would be interesting to see the simulation prototype programmed in another platform (e.g. RePast Simphony). We did however put our result of the first stage model simulation next to the solution of the same problem solved with another methodology – an optimisation model – and we may state that the agent-based approach stood strongly in the comparison.

Clearly we leave a lot of questions concerning the verification and validation of agent-based models in general, and our prototype model in particular, unanswered. On the one hand because our prototype model is not based on empirical data; on the other hand because the developments in the discipline are still recent and there are not yet unified standards for verification and validation to comply with.

6. Conclusion

In retail practice we observe that evolving consumer (spatial) behaviour drives the strategic and logistical operations management decisions of large retailing companies. To study one particular aspect of this phenomenon, changing retail location patterns, we were confronted with a discrepancy between the modelling of the supply side and the demand side. To integrate the recent challenges of bounded rationality and mobility in the consumer spatial behaviour with the complex environment in which location decisions are to be taken on the supply side, we proposed an agent-based approach.

The first study in the discipline of ABMS for social sciences is quite recent when compared to the tradition of operations research methods. And although the field gains increasing popularity, the applications of modelling location decisions in retail context are still rare. Therefore we proposed a conceptual model and implemented the simulation model in an artificially generated world. We ran the model for five iterative stages of incremental development and this showed the interplay between the consumer spatial behaviour and retailer location models. By taking the point of view of the decision makers, we ended the simulation as soon as all location decisions were taken. A next step in the study would be to watch the world develop to a certain type of stability in the spatial competition between the retailer and his competitor.

This illustrates that our model scores as laboratory experimental on maturity degree. It is recommended to further study the robustness and the sensitivity of the implementation and we would love to apply and calibrate the simulation to real world data. This, however, requires a lot of information from both the demand and supply side of a retail market, but is not impossible given the increasing availability of huge amounts of geo-referenced panel and business data. Such a real-world validation would also require implementing the model against the background of a GIS. That evolution is momentarily coming to full bloom in the domain of social simulation and the preliminary available results look very promising.

Acknowledgements

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References

Axtell, R., Axelrod, R., Epstein, J.M., & Cohen, M.D. 1996. Aligning simulation models: A case study and results. *Computational & mathematical organization theory,* 1(2), 123–141.

Balmer, M., Cetin, N., Nagel, K. & Raney, B. 2004. Towards Truly Agent-Based Traffic and Mobility Simulations. *Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems.* 1(1), 60–67.

Berman, O., & Krass, D. 1998. Flow intercepting spatial interaction model: a new approach to optimal location of competitive facilities. *Location science*, 6(1-4), 41–65.

Church, R., & ReVelle, C. 1974. The maximal covering location problem. *Papers in regional science*, 32(1), 101–118.

Dion, D., & Cliquet, G. 2006. Consumer spatial behavior. Pages 29–56 of: Cliquet, G. (ed), *Geomar- keting: methods and strategies in spatial marketing*. ISTE.

Douglas, S. P., & Craig, C. S. 1997. The changing dynamic of consumer behavior: implications for cross-cultural research. *International journal of research in marketing*, 14(4), 379–395.

Drezner, T., & Eiselt, H.A. 2002. Consumers in competitive location models. pp. 151–178 of: Drezner, Z., & Hamacher, H. (eds), *Facility location: Applications and theory*. Springer, Berlin Heidelberg.

Fagiolo, G., Birchenhall, C., & Windrum, P. 2007. Empirical validation in agent-based models: Introduction to the special issue. *Computational economics*, 30(3), 189–194.

Jager, W. 2006. *Simulating consumer behaviour: a perspective*. Tech. rept. Netherlands Environmental Assessment Agency.

Macal, C, North, M. 2010. Tutorial on agent-based modelling and simulation. *Journal of simulation*, 4 (3), 151–162.

McNally, M. 2000. The activity-based approach. pp. 53-69 Of: Hensher, D. & Button, K. (eds), *Handbook on Transportation Modelling*. Elsevier, UK.

Marks, R. 2007. Validating simulation models: A general framework and four applied examples. *Computational economics*, 30(3), 265–290.

Midgley, D., Marks, R., & Kunchamwar, D. 2007. Building and assurance of agent-based models: An example and challenge to the field. *Journal of business research*, 60(8), 884–893.

Moss, S., & Edmonds, B. 2005. Sociology and simulation: Statistical and qualitative cross-validation. *American journal of sociology*, 110(4), 1095–1131.

Vanhaverbeke, L. *Competitive location models and consumer spatial behaviour: Optimization models and an agent based approach*; PhD dissertation, VUBPress, Brussels, 2010.

Wilensky, U. 2009. *NetLogo 4.1 User Manual*. Tech. rept. Center for Connected Learning and Computer-Based Modeling, Northwestern University. Evanston, IL, http://ccl.northwestern.edu/netlogo/.Tutorial on agent-based modelling and simulation.